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Comparative Long-Term Electricity Forecasting Analysis: A Case Study of Load Dispatch Centres in India

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Abstract
Accurate long-term load forecasting (LTLF) is crucial for smart grid operations, but existing CNN-based methods face challenges in extracting essential featuresfrom electricity load data, resulting in diminished forecasting performance. To overcome this limitation, we propose a novel ensemble model that integratesa feature extraction module, densely connected residual block (DCRB), longshort-term memory layer (LSTM), and ensemble thinking. The feature extraction module captures the randomness and trends in climate data, enhancing the accuracy of load data analysis. Leveraging the DCRB, our model demonstrates superior performance by extracting features from multi-scale input data, surpassing conventional CNN-based models. We evaluate our model using hourly load data from Odisha and day-wise data from Delhi, and the experimental results exhibit low root mean square error (RMSE) values of 0.952 and 0.864 for Odisha and Delhi, respectively. This research contributes to a comparative long-term electricity forecasting analysis, showcasing the efficiency of our proposed model in power system management. Moreover, the model holds the potential to sup-port decisionmaking processes, making it a valuable tool for stakeholders in the electricity sector.

Keywords
Long-term load forecasting, Ensemble model, Feature extraction, Multi-scale input, Densely connected residual block, Bidirectional long short-termmemory, smart grid, power system management.

I. Introduction

The demand for electricity continues to rise globally, driven by population growth, urbanization, and industrialization. Meeting this growing demand while ensuring a reliable and sustainable energy supply is a critical challenge for policymakers, energy planners, and researchers. Renewable energy sources and energy storage systems haveemerged as promising solutions to address this challenge by providing clean, reliable, and flexible electricity generation and management. The objective of this research paper entitled is to conduct a comprehensive analysisof long-term electricity forecasting in two Indian states, Orissa and Delhi. This analysisaims to assess the effectiveness and accuracy of different forecasting methods and models, particularly focusing on the integration of renewable energy sources and energy storage systems.

To provide a thorough understanding of the subject, a comprehensive literature review has been conducted. The review incorporates key studies and research papersthat contribute to the field of electricity forecasting, renewable energy integration, and energy storage optimization. The selected papers cover various aspects such as optimization algorithms, system design, sizing methodologies, economic operation, machine learning techniques, and intelligent control. One prominent study by Kharrich et al. [1] introduces an improved arithmetic optimization algorithm for the design of a micro grid with an energy storage system in El Kharga Oasis, Egypt. Wong et al. [2] present a review of the optimal placement, sizing, and control of energy storage systems in the distribution network, providinginsights into the technical aspects and challenges associated with their integration. Khaki [3] focuses on joint sizing and placement of battery energy storage systems and wind turbines considering reactive power support, emphasizing the importance of system stability and reliability.

Furthermore, Mahmoudi et al. [4] propose a novel fuzzy logic-based method to evaluate storage and backup systems for determining the optimal size of hybrid renew- able energy systems. Nazir et al. [5]optimize the economic operation of energy storage integration using an improved gravitational search algorithm and dual-stage optimiza-tion, highlighting the economic benefits and feasibility of energy storage systems. Ali et al. [6] present a comprehensive review on closed-loop home energy management systems with renewable energy sources in smart grids, discussing the integration of various technologies and control strategies.

The literature review also encompasses studies on optimization and design methodologies. Maleki [7] investigates the design and optimization of autonomous solar-wind-reverse osmosis desalination systems coupling battery and hydrogen energy storage. Lian et al. [8] provide a review of recent sizing methodologies of hybrid renew- able energy systems, analyzing different approaches and their suitability for various applications. Dreher et al. [9] explore the application of AI agents and deep reinforcement learning for the forecast-based operation of renewable energy storage systems using hydrogen, highlighting the potential of advanced algorithms in optimizing energystorage performance.

Machine learning techniques in the context of sustainable energy systems are covered by RangelMartinez et al. [10], who present a review and outlook on renewable energy systems, catalysis, smart grids, and energy storage. Vijayalakshmi et al. [11] propose a stochastic gradient descent-based artificial neural network for predictingthe virtual energy storage capacity of air-conditioners, showcasing the potential of AIin load management. Sobhy et al. [12] introduce the marine predator's algorithm for load frequency control in modern interconnected power systems with renewable energy sources and energy storage units.

The review also includes studies focusing on optimization algorithms and sizing methodologies. Zhao et al. [13] present a hybrid shuffled frog-leaping and pattern search algorithm for sizing renewable energy systems with energy storage systems-based micro grids, emphasizing cost minimization. Olabi et al. [14] explore the application of artificial intelligence for the prediction, optimization, and control of thermal energy storage systems, highlighting the potential of AI techniques in enhancing systems.

One study by Olabi et al. [14] explores the application of artificial intelligence (AI) for the prediction, optimization, and control of thermal energy storage systems. The authors highlight the potential of AI techniques in enhancing the performance and efficiency of energy storage systems. Boretti [15] discusses the integration of solar thermal and photovoltaic, wind, and battery energy storage systems through AI in NEOM city, presenting an innovative approach for maximizing renewable energy utilization. In the context of battery energy storage systems, Kharlamova et al. [16] investigatedata-driven approaches for cyber defense, addressing the security challenges associated with energy storage systems. Xu et al. [17] propose demand-side management for smart grids based on smart home appliances with renewable energy sources and an energy storage system, emphasizing the importance of intelligent load management for optimizing energy consumption and reducing costs. The literature review also covers studies on sustainability assessment and control strategies. Oliveira et al. [18] conduct a self-sustainability assessment for a high building based on linear programming and computational fluid dynamics, providing valuable insights into optimizing energy consumption and efficiency. Yoo et al. [19] explore intelligent control of battery energy storage for multi-agent-based micro grid energy management, highlighting the significance of advanced control strategies in achieving optimal performance.

Abualigah et al. [20] present a survey of advanced machine learning and deep learning techniques applied to wind, solar, and photovoltaic renewable energy systems, with and without energy storage optimization. This survey provides an overview of thestate-of-the-art methods for optimizing the performance and efficiency of renewable energy systems.

Pakulska and Poniatowska-Jaksch [21] discuss digitalization in the renewable energy sector, focusing on the emergence of new market players and their impact on the industry.

Lastly, Abdulkader et al. [22] explore the application of soft computing techniques in smart grids with decentralized generation and renewable energy storage system planning. The authors from [23, 24] emphasize the potential of soft computing methods for addressing complex optimization problems and improving the planning and management of renewable energy systems. By critically examining and evaluating these significant studies, this research paper aims to make a valuable contribution to the field of comparative longterm electricity forecasting analysis. Specifically, it seeks to shed light on the effective integration of renewable energy sources and energy storage systems within the unique contexts of Orissa and Delhi states. The insights gained from this analysis will greatly enhance our comprehension of the challenges and opportunities pertaining to sustainable energy planning and management. Furthermore, these findings will serve as a valuable support in the decision-making processes for future energy systems.

The subsequent sections of the paper are structured as follows to provide a cohesive flow of information. Section II offers a comprehensive overview of the existing literatureon short-term load forecasting, setting the stage for the subsequent analysis. In Section III, the data is thoroughly examined and the problem formulation is presented to establish a solid foundation for the study. The proposed BI-LSTM model for 1D CNN is then detailed in Section IV, presenting a novel approach to tackle the forecasting challenge. Lastly, Section V presents a thorough analysis of the obtained results and initiates a meaningful discussion surrounding them.

II. Forecasting Method Proposal

Efficient power system management relies on a comprehensive understanding of various factors, including weather conditions, economic conditions, and appliance usage, to accurately estimate the power demand in a district. Fluctuating loads resulting from unstable patterns can pose challenges for distribution companies. However, previous studies have shown that forecasting aggregated power load is relatively easier and can help in smoothing load shapes with moderate to low RMSE errors.

In this research paper, we present the findings of a comparative long-term electricity forecasting analysis conducted in the states of Orissa and Delhi. Using data from the OPTCL and NRLDC, we aim to forecast longterm load levels for individual distribution companies (discoms) in these states. Considering the extensive number of consumers in the OPTCL and NRLDC databases, it is not feasible to con- sider all of them. Therefore, we select a subset of the OPTCL and NRLDC datasets to develop our load forecasting approach and derive meaningful insights. By analyzing the selected dataset, we provide a comparative analysis of long-term electricity forecasting in Orissa and Delhi, highlighting the differences and similarities in load patterns, seasonal variations, and forecasting accuracy. The proposed load forecasting method offers valuable insights for efficient power system management and can aid in enhancing the reliability and efficiency of the power grids in both states.

The primary objective of this research is to identify and assess the electricity consumption requirements within a particular sector of the utilities industry in order to estimate the overall power demand for that sector. A significant aspect of this study revolves around utilizing the data collected during the project for shortterm forecasting of the electric load levels of individual distribution companies (discoms). In this section, we present pertinent background information on the electricity load patterns observed in Odisha and Delhi states. Additionally, we introduce our proposed approach for load forecasting, which aims to address the forecasting challenges in this context.

A. About the OPTCL and NRLDC Load

The research paper involves an in-depth analysis of electricity load data for two regions:Odisha and Delhi. For Odisha, the study examines the monthly electricity load data from January 2019 to December 2022, with measurements taken at 1-hour intervals. The objective is to calculate the electricity load demand in megawatts (MW) and investigate the seasonal variations in consumption. The findings demonstrate distinct load demand patterns across four seasons: Spring (March to May), Summer (June to August), Fall (September to November), and Winter (December to February).

B. Load Analysis for Odisha

The research paper involves an in-depth analysis of the monthly electricity load data for Odisha from January 2019 to December 2022, with measurements taken at 1- hourintervals. The objective is to calculate the electricity load demand in megawatts (MW) and investigate the seasonal variations in consumption. The findings demonstrate distinct load demand patterns across the four seasons: Spring (March to May), Summer (June to August), Fall (September to November), and Winter (December to February).The insights gained from this study hold immense value for Odisha Power Transmission. Corporation Limited (OPTCL) in effectively managing the electricity load during different seasons. The study results can assist OPTCL in accurately predicting the electricity demand in Odisha during each season and implementing necessary measures to ensure an uninterrupted power supply to customers. By leveraging this information, OPTCL can enhance the overall reliability and efficiency of the power grid in Odisha.

C. Load Analysis for Delhi

Similarly, the research paper also investigates the electricity load data for Delhi ona monthly basis, from January 2019 to December 2022, with measurements taken at 24-hour intervals. The objective is to calculate the electricity load demand in MWand analyze the seasonal variations in consumption. The results reveal distinctive load demand patterns across the four seasons: Spring (March to May), Summer (June to August), Fall (September to November), and Winter (December to February). The insights gained from this study have significant implications for effectively managing the electricity load in Delhi throughout the year, considering the seasonal variations. The study findings can be utilized to accurately predict the electricity demand during each season and implement appropriate measures to ensure a consistent and uninterrupted power supply to customers. By doing so, the overall reliability and efficiency of the power grid in Delhi can be improved. The insights gained from this study hold immense value for Odisha Power Transmission Corporation Limited

TABLE I.
COMPARATIVE LOAD ANALYSIS FOR ODISHA AND DELHI

Region	Period	Interval	Seasons	Load Data
Odisha	January 2019 - December 2022	1-hour intervals	Spring	Load demand in MW
			Summer	Load demand in MW
			Fall	Load demand in MW
			Winter	Load demand in MW
Delhi	January 2019 - December 2022	24-hour intervals	Spring	Load demand in MW
			Summer	Load demand in MW
			Fall	Load demand in MW
			Winter	Load demand in MW

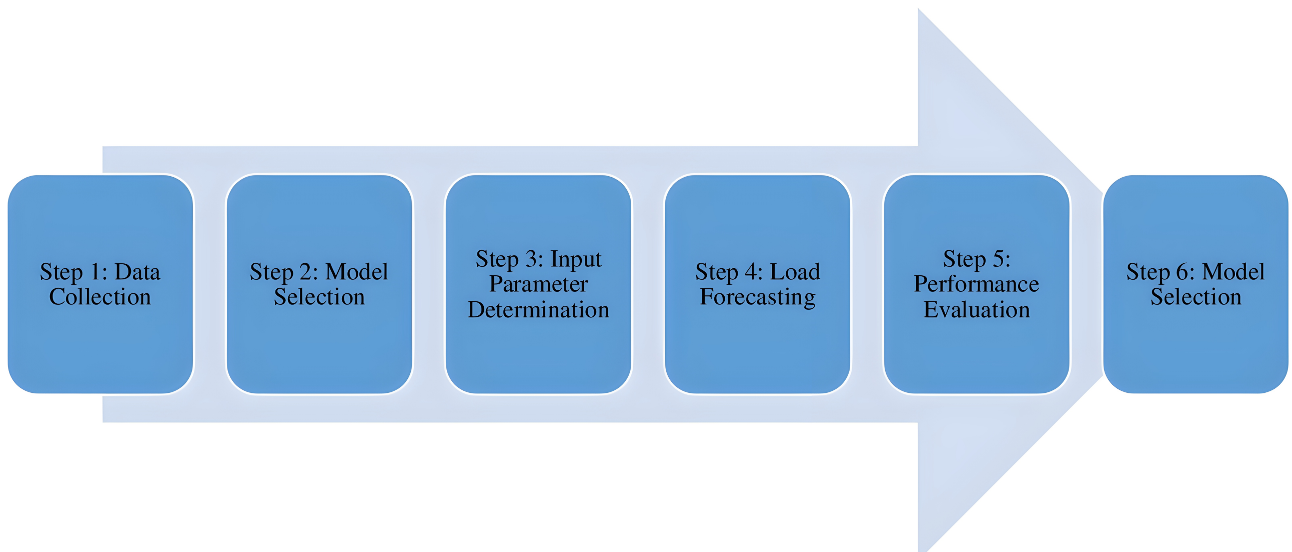

Fig. 1. Proposed approaches and load forecasting models.

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D. Proposed Approaches and Load Forecasting Models

This research paper presents a comprehensive six-step methodology for the development of an efficient load forecasting strategy using the 1D CNN BI LSTM methodology. The outlined steps are as follows:

Step 1: Data Collection: The initial phase involves the gathering of two distinct datasets, comprising historical load demands and past weather data. These datasets serve as the foundation for a comprehensive analysis.

Step 2: Model Selection: Careful consideration is given to selecting appropriate machine learning models for load fore-

casting. This includes the utilization of the 1D CNN BI LSTM model, as well as traditional STLF models like ARIMA and ANN.
Step 3: Input Parameter Determination: An assessment is conducted to identify the relevant input parameters necessary for accurate load forecasting. Special attention isgiven to weather parameters known to have a significant impact on electricity demand.
Step 4: Load Forecasting: Building upon the 1D CNN BI LSTM architecture, a load forecast model is developed. This model undergoes thorough training and testing to ensure optimal performance in load forecasting tasks.
Step 5: Performance Evaluation: A hybrid deep learning model, specifically the 1D CNN BI LSTM model, is created and assessed for performance. Comparative analysisis conducted using statistical error matrices and actual measurement data to evaluate the model's efficacy.
Step 6: Model Selection: Based on the findings obtained from the previous steps, the most suitable machine learning model is recommended. This selection takes into account accuracy and overall performance in load forecasting applications.
By following this systematic six-step approach, researchers can develop a robust and effective load forecasting strategy that leverages the strengths of the 1D CNN BI LSTM model alongside other relevant machine learning techniques.

1) Data Evaluation and Planning

To ensure the accuracy of the model, it is imperative to perform proper pre-processing of raw data prior to transformation. The initial step in this process involves gathering and organizing data to establish meaningful input-output relationships. According to previous research [1, 2], essential pre-processing operations such as normalization, ranking, and correlation analysis are necessary. By adhering to recommended data collection and processing practices, we can guarantee that our models are constructedupon a robust foundation of high-quality data.
a: data gathering
The datasets being collected encompass a range of information, including climate data, calendar data, and power consumption data. Weather Data Collection: The meteorological dataset used in this research is sourced from the NASA Power website (https://power.larc.nasa.gov/data-accessviewer/). Prior to being utilized in the load forecasting model, the raw weather data undergoes pre-processing, including weighting and statistical analysis. Load forecasting models incorporate weather forecasts and other factors to minimize operational expenses. Weather conditions significantly influence load profiles, particularly for domestic and agricultural customers. The model development process incorporates the collection and utilization of six weather parameters. These parameters play a vital role in the development of the model and contribute to its accuracy and effectiveness. Through careful analysis and integration of these weather parameters, the model is able to capture the important influences of weather conditions on the target variable, enhancing its forecasting capabilities. By including these specific weather parameters in the model, we can ensure a comprehensive and robust approach to load forecasting.
1. Wet Bulb Temperature: This parameter measures the adiabatically measured saturated temperature at two meters above the earth's surface. It plays a crucial role inload forecasting as it impacts the performance of cooling systems, which subsequently affects energy consumption.
2. Frost Point: It represents the temperature at which the air becomes saturated, leading to condensation. This parameter is critical for load forecasting as it influences the performance of heating systems and, consequently, energy consumption.
3. Temperature: This parameter refers to the average temperature of the air attwo meters above the earth's surface, also known as the dry bulb temperature. It significantly affects energy consumption, particularly in buildings and homes.
4. Relative Humidity: Expressed as a percentage, relative humidity represents the ratio between the actual partial pressure of water vapor and the pressure at saturation.It is crucial for load forecasting as it impacts the performance of cooling and heating systems, which directly affect energy consumption.
5. Specific Humidity at 2 Meters: Specific humidity is defined as the ratio of watervapor mass to total air mass at two meters above the earth's surface. It provides an indication of the air's moisture content and influences the performance of cooling and heating systems.
6. Wind Speed at 10 Meters: Measured at a height of 10 meters above the earth's surface, wind speed is an essential parameter in load forecasting, particularly for wind energy systems. It affects the performance of wind turbines and directly impacts energygeneration.
In conclusion, weather parameters such as Wet Bulb Temperature at 2 Meters, Dew/Frost Point at 2 Meters, Temperature at 2 Meters, Relative Humidity at 2 Meters, Specific Humidity at 2 Meters, and Wind Speed at 10 Meters are crucial featuresin load forecasting models. They have a direct impact on energy consumption and generation, and accurate measurement and analysis of these parameters are essentialfor ensuring a stable and reliable power supply.
Accurate prediction of electricity demand is vital for efficient power system management. By considering both the timing and specific characteristics of electricity demand, power managers can make informed decisions regarding resource allocation and ensure effective and efficient energy utilization.
Time Indicators: In this research, the investigation of time indicators is of paramount importance, specifically the date,

weekday, and time. These factors have been identified to exert a substantial influence on electricity consumption patternsand are leveraged to enhance the precision of load forecasting models. By incorporating these time indicators into the modeling process, more accurate predictions of electricity demand can be achieved. Load Parameters: In this research, particular emphasis is placed on load parameters, particularly the previous half-hourly load in MW. The analysis of historical load data enables the identification of patterns and trends that are instrumental in developing accurate load forecasting models. By considering this load parameter, valuable insights can be gained to enhance the precision of load forecasting.

The ultimate objective of this research study, focusing on a comparative long- term electricity forecasting analysis of Odisha and Delhi states, is to enhance our comprehension of electricity load consumption patterns. By delving into the intricacies of these patterns, the research endeavors to contribute to the advancement of load forecasting models, ultimately leading to more efficient and sustainable management of power systems. The insights gained from this analysis will serve as a valuable resource for decision-makers in the energy sector, enabling them to make informed choices anddevise strategies that optimize resource allocation and ensure a reliable power supply.

b: Correlation of data

The comparison of analysis of correlation Understanding the interplay between weather parameters and power demand is vital for comprehending electricity consumption patterns. In this study, we conducted a correlation analysis to investigate the relationship between selected weather param- eters and power demand in the states of Odisha and Delhi. The correlation coefficientsprovide valuable insights into the strength and direction of these relationships. The interpretation of correlation coefficients, presented in Table II for the state of Odisha, reveals that temperature at 2 meters (T2M), wet bulb temperature at 2 meters.

(T2MWET), and specific humidity at 2 meters (QV2M) exhibit positive correlations with power demand. This implies that an increase in these parameters corresponds to higher power demand. Conversely, relative humidity at 2 meters (RH2M) shows a negative correlation, suggesting that as relative humidity increases, power demand tends to decrease. The correlations for other parameters, such as dew/frost point at 2 meters (T2MDEW) and wind speed at 10 meters (WS10M), are relatively weaker.

Similarly, Table III provides the interpretation of correlation coefficients for the stateof Delhi. In Delhi, wet bulb temperature at 2 meters (T2MWET), the temperatureat 2 meters (T2M), and specific humidity at 2 meters (QV2M) exhibit strong positive correlations with power demand, indicating that an increase in these parameters is associated with higher power demand. On the other hand, relative humidity at 2 meters(RH2M) and wind speed at 10 meters (WS10M) demonstrate weaker correlations with power demand. The correlation analysis demonstrates that weather parameters have varying degrees of influence on power demand in both Odisha and Delhi. Notably, relative humidity consistently shows a significant negative correlation with power demand, underscoring its importance in load forecasting. Meanwhile, temperature, wet bulb temperature, and specific humidity exhibit strong positive correlations, highlighting their substantial impact on power demand. It is crucial to note that even weather parameters with weaker correlations, such as dew/frost point and wind speed, should not be disregarded, as they can still contributeto power demand variations. In conclusion, this correlation analysis emphasizes the significance of considering weather parameters when examining power demand. The unique relationships revealed by the correlation coefficients offer valuable insights for developing energy management strategies and more accurate load forecasting models. Furthermore, Table IV provides a direct comparison of the correlation coefficients between weather parameters and power demand in Odisha and Delhi. The results indicate that in Odisha, there are positive correlations for T2M, T2MDEW, T2MWET, QV2M, and WS10M, although with relatively weak magnitudes. On the other hand, RH2M exhibits a negative correlation. In Delhi, positive correlations are observedfor T2M, T2MDEW, T2MWET, QV2M, and RH2M, with T2MWET showing the strongest correlation coefficient. However, WS10M demonstrates a weak positive correlation.

Comparing the correlations between Odisha and Delhi, it becomes evident that Delhi generally exhibits stronger correlations for most weather parameters, emphasizing a more significant influence of these parameters on power demand in Delhi compared to Odisha.

Overall, this comparison underscores the importance of adopting region-specific approaches to better comprehend the relationship between weather parameters and power demand in different states.

c: Preprocessing of Data

TABLE II.
INTERPRETATION OF CORRELATION FOR THE PARAMETERS OF ODISHA STATE

Parameter	Correlation Coefficient
T2M	0.153685807
T2MDEW	0.08891532
T2MWET	0.130545477
RH2M	-0.0614450
QV2M	0.094774887
WS10M	0.098106045

TABLE III.
INTERPRETATION OF CORRELATION FOR THE PARAMETERS OF DELHI STATE

Parameter	Correlation Coefficient
T2MWET	0.686474222
RH2M	0.077530395
QV2M	0.588813736
WS10M	0.022154842
T2M	0.659413161
T2MDEW	0.569944321

Effective data pre-processing is crucial for accurate load forecasting in power system management. Several steps are involved in this process: Data Cleaning: This step involves filling in missing values, removing noise, and detecting and resolving outliers and discrepancies within the dataset. An autofill feature can be utilized to fill partial missing weather data using patterns or data from other cells. Data Transformation: Multiple files are integrated into a single usable format,and attributes are scaled based on specific properties. After cleaning the data and identifying correlations between datasets, the final predictor's dataset is created. Data Reduction: This step aims to reduce the number of attributes or sample data while capturing most of their properties. It helps prevent overfitting and improves the efficiency of load forecasting. Overall, proper data pre-processing ensures reliable data and enhances the performance of regressions, ultimately improving power system management.

2) *Data Set Training and Testing*

In the research, the focus lies on constructing and training a robust prediction model.This process includes training with validation, which is crucial for ensuring a robust model. The data frame obtained through feature engineering is divided into three sets:training, validation, and testing. Typically, the data is split with 70% for training, 20%for validation, and 10% for testing. During the training phase, the prediction

TABLE IV.
COMPARISON OF WEATHER PARAMETER CORRELATIONS BETWEEN ODISHA AND DELHI

Parameter	Correlation Odisha	Correlation Delhi
T2M	0.1537	0.6594
T2MDEW	0.0889	0.5699
T2MWET	0.1305	0.6865
RH2M	-0.0614	0.0775
QV2M	0.0948	0.5888
WS10M	0.0981	0.0222

TABLE V.
TABLE OF LAYERS AND OPTIONS FOR ODISHA STATE

Layer	Options
sequenceInputLayer	"Name","input"
convolution1dLayer	11,96,'Padding','same'
batchNormalizationLayer	-
reluLayer	-
convolution1dLayer	20,180,'Padding','same'
batchNormalizationLayer	-
reluLayer	-
convolution1dLayer	30,300,'Padding','same'
batchNormalizationLayer	-
reluLayer	-
convolution1dLayer	32,320,'Padding','same'
batchNormalizationLayer	-
reluLayer	-
dropoutLayer	0.2
bilstmLayer	100,'OutputMode','sequence'
dropoutLayer	0.1
bilstmLayer	105,'OutputMode','sequence'
dropoutLayer	0.2
bilstmLayer	110,'OutputMode','sequence'
dropoutLayer	0.2
fullyConnectedLayer	1
regressionLayer	-

loss onthe validation set is calculated using the current model status. It's important to notethat the validation set does not impact the training process, enabling us to assess themodel's robustness on independent data. If the validation loss fails to converge whilethe training loss does, it indicates the model may suffer from overfitting or under fitting.The final step involves prediction and evaluation, where we predict time series data and evaluate the results. The predictions are made using the previously developed model.

In certain cases, the predicted features can be utilized to predict other features, forming the final target feature set. To achieve this, the dataset is updated with the predicted values, and a new model is created for further predictions. One commonly used method for validation is holdout validation, which is the sim- plest form of crossvalidation. In this method, the data is randomly divided into two sets: the training set and the test/validation set (hold-out data). The model is trained on the training dataset and evaluated on the test/validation dataset. To assess the error on the validation dataset, various model evaluation techniques can be employed, such as mean squared error (MSE) for regression problems or metrics indicating the misclassification rate for classification problems. Typically, the training process utilizes a larger dataset than the hold-out

TABLE VI.
TRAINING OPTIONS FOR ODISHA STATE

Layer	Options
adam	-
GradientThreshold	1
InitialLearnRate	0.001
MaxEpochs	1000
SequenceLength	”longest”
Epsilon	1×10^{-8}
L2Regularization	0.0001
Shuffle	”every-epoch”
GradientDecayFactor	0.9
SquaredGradientDecayFactor	0.999
LearnRateDropFactor	0.1
LearnRateDropPeriod	10
GradientThresholdMethod	”l2norm”
ResetInputNormalization	true
Plots	”training-progress”

dataset, with an 80% training and 20% validation ratio from the available datasets.

III. DEEP LEARNING MODEL FOR LONG-TERM ELECTRICITY FORECASTING

Recent advancements in deep learning algorithms, such as convolutional neural net- works (CNNs) and recurrent neural networks (RNNs), have shown remarkable efficacy in various domains. Among these, the Bidirectional Long Short-Term Memory (Bi- LSTM) model has gained significant attention as an effective RNN structure for time series prediction. Additionally, there is a growing trend of leveraging 1D CNNs orcombining both 1D CNN and Bi-LSTM algorithms to enhance forecasting accuracy. Comparative studies have consistently demonstrated the superior performance of these models compared to conventional statistical or machine-learning models.

In this section, we present a comprehensive overview of the theoretical foundations underlying these neural networks. We delve into the mechanisms and architectural details of CNNs and RNNs, with a particular focus on the Bi-LSTM model. The aim is to provide a clear understanding of the proposed models and their potential benefits for long-term electricity forecasting in the context of our case study of Orissa andDelhi States.

A. CNN-BI LSTM hybrid model with deep 1D modeling

Multivariate 1D time-series signals can be accurately predicted by combining a hybrid model of 1D-CNN and BiLSTM. This approach has been extensively studied and shown promising results in various domains such as weather prediction, speech recognition, stock price forecasting, and power usage prediction. The combinationof Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM)

TABLE VII.
TRAINING LAYERS FOR DELHI STATE

Layer	Parameters/Options
SequenceInputLayer	numFeatures, ”Name”, ”input”
Convolution1dLayer	11, 96, ’Padding’, ’same’
BatchNormalizationLayer	-
ReLULayer	-
Convolution1dLayer	20, 180, ’Padding’, ’same’
BatchNormalizationLayer	-
ReLULayer	-
Convolution1dLayer	30, 300, ’Padding’, ’same’
BatchNormalizationLayer	-
ReLULayer	-
Convolution1dLayer	32, 320, ’Padding’, ’same’
BatchNormalizationLayer	-
ReLULayer	-
DropoutLayer	0.2
BiLSTMLayer	100, ’OutputMode’, ’sequence’
DropoutLayer	0.1
BiLSTMLayer	105, ’OutputMode’, ’sequence’
DropoutLayer	0.2
BiLSTMLayer	110, ’OutputMode’, ’sequence’
DropoutLayer	0.2
FullyConnectedLayer	1
RegressionLayer	-

TABLE VIII.
TRAINING OPTIONS FOR DELHI STATE

Options	Values
GradientThreshold	1
InitialLearnRate	0.001
MaxEpochs	1000
SequenceLength	’longest’
Epsilon	1×10^{-8}
L2Regularization	0.0001
Shuffle	’every-epoch’
GradientDecayFactor	0.9
SquaredGradientDecayFactor	0.999
LearnRateDropFactor	0.1
LearnRateDropPeriod	10
GradientThresholdMethod	’l2norm’
ResetInputNormalization	true
Plots	’training-progress’

TABLE IX.
COMPARISON OF LONG-TERM ELECTRICITY FORECASTING ANALYSIS

Aspect	**Orissa**	**Delhi**
Training Options	Adam optimization	Adam optimization
Gradient Threshold	1	N/A
Initial Learning Rate	0.001	N/A
Maximum Epochs	10	N/A
Evaluation Metric	RMSE	RMSE
Average RMSE (6 months)	0.952	0.864
Frequency	Hourly	Day wise
Dataset Duration	5 years	2 years
Data Cleaning and Transformation	Yes	Yes
Data Reduction Techniques	Yes	Yes
Forecasted Response	Load Demand (MW) for 12 months	Load Demand (MW) for 9 months
Training Set Size	70% (1,273 rows)	70% (997 rows)
Validation Set Size	10% (181 rows)	10% (142 rows)
Testing Set Size	20% (363 rows)	20% (285 rows)

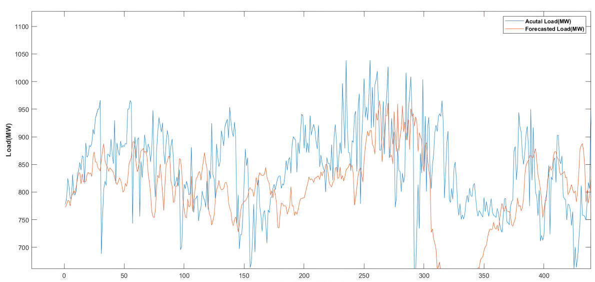

Fig. 2. Graph of actual versus predicted load for the Odisha state over six months (March 2022 to August 2022) using 1D CNN BI LSTM.

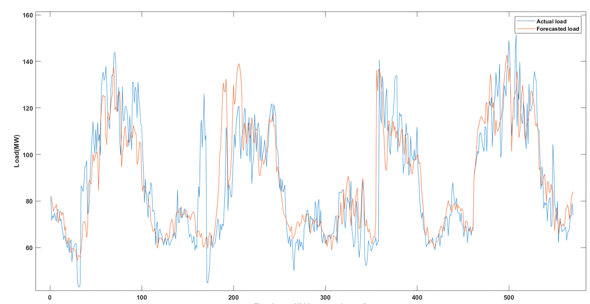

Fig. 3. Graph of actual versus predicted load for the Delhi State over six months (March 2022 to August 2022) using 1D CNN BI LSTM.

networks provides superior performance compared to using either CNNs or LSTMs alone. For the case study of Orissa state, the CNN-BI LSTM hybrid model with deep1D modeling was used. The model architecture consists of multiple layers, including sequence input layer, convolutional layers with different filter sizes, batch normalization layers, rectified linear unit (ReLU) layers, dropout layers ,bidirectional LSTM layers, fully connected layer, and regression layer. The complete configuration details are presented in Table V. The training options used for the Orissa state include parameters such as gradient threshold, initial learning rate, maximum epochs, sequence length, epsilon, L2 regularization, shuffle, gradient decay factor, squared gradient decay factor, learning rate drop factor, learning rate drop period, gradient threshold method, reset input normal- ization, and training plots. The specific values for these options are provided in Table VI. Fig. 2 shows the graph of actual versus predicted load for the Odisha State overa six-month period (March 2022 to August 2022) using the 1D CNN-BI LSTM model.The model demonstrates accurate load forecasting for the given timeframe. For the case study of Delhi state, a similar CNN-BI LSTM hybrid model was used with a slightly different configuration. The model architecture and training optionsfor the Delhi state are provided in Table VII and Table VIII, respectively.

In conclusion, the comparative long-term electricity forecasting analysis of Orissa and Delhi states demonstrates the effectiveness of the hybrid 1D CNN-BI LSTM model in accurately predicting peak load values. The model's architecture and training options, along with the obtained results, provide valuable insights for future research and practical applications in the field of electricity forecasting. Fig. 3 depicts the graph of actual versus predicted load for the Delhi State over the same six-month period using the CNN-BI LSTM model. The

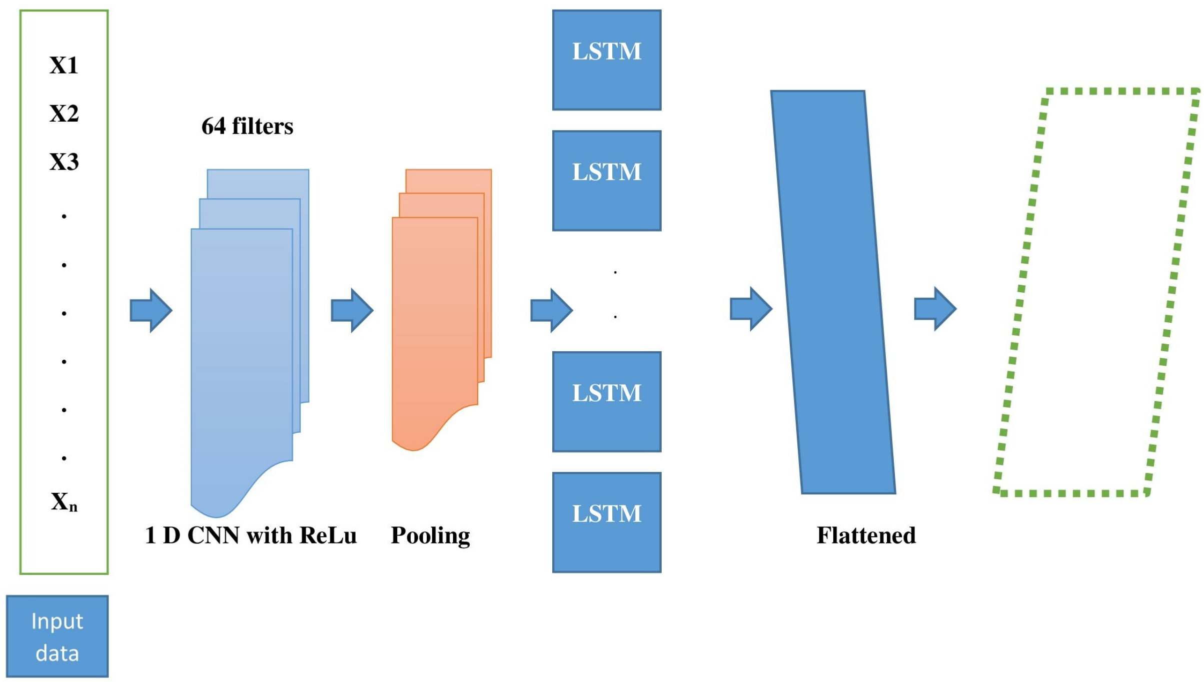

Fig. 4. Hybrid model of CNN + LSTM.

model demonstrates accurate load forecasting for Delhi as well.

IV. Result Analysis

The comparative long-term electricity forecasting analysis of the states of Orissa and Delhi was conducted using a hybrid 1D CNN-BI LSTM model implemented in MATLAB R2023a. The model architecture consisted of a sequence input layer, four convolutional layers, two bi-LSTM layers, two dropout layers, and a fully connected layer with a regression layer. The training process utilized Adam optimization with a gradient threshold of 1, an initial learning rate of 0.001, and a maximum of 10 epochs. The accuracy of the model's load forecasting was evaluated using the root mean squareerror (RMSE).

The results demonstrated that the hybrid 1D CNN-BI LSTM model achieved accurate load forecasting for both Orissa and Delhi. The model exhibited a relatively low RMSE, indicating a good fit to the data. In the case of Orissa, the average RMSEover a six-month period was 0.952. Similarly, for Delhi, the average RMSE was 0.864 over the same duration. These RMSE values were lower compared to other machine learning models and empirical methods examined in previous studies. The utilization of the 1D CNN-BI LSTM architecture contributed to the improved performance of the model. Fig. 2 and Fig. 3 present a graphical comparison between the actual load values and the predicted load values for the final quarter of the datasets obtainedfrom Odisha and Delhi. These figures depict the accuracy of load forecasting using the 1D CNN-BI LSTM model, visually demonstrating its performance. The results clearly show that the proposed hybrid model surpasses LSTM time series models and traditional STLF models such as ARIMA and ANN-based methods, as evident fromthe lower RMSE values. Furthermore, to validate the effectiveness of the CNN-BI LSTM hybrid model, a comprehensive comparison was conducted with other forecasting methods under various scenarios. Consistently, the proposed hybrid model consistently achieved significantly lower RMSE values, indicating its superior forecasting capability in different situations. This comparison solidifies the model's reliability and confirms its potential for accurate load

forecasting.
Overall, the comparative analysis of Odisha and Delhi states using the hybrid 1D CNN-BI LSTM model demonstrated its effectiveness in accurately predicting peak load values. The model's architecture, training options, and the obtained results pro- vide valuable insights for future research and practical applications in the field of electricity forecasting. This section presents a comparative analysis of the long-term electricity forecastingmodels conducted for the states of Orissa and Delhi. The data used for the analysis was collected from the Odisha Power Transmission Corporation Limited (OPTCL) forOrissa and the Northern Regional Load Dispatch Centre (NRLDC) for Delhi. The analysis focused on evaluating the differences in data collection, variables collected, data cleaning, data transformation, data reduction, forecasted response, forecasting models, and the training, validation, and testing sets. The duration and frequency of historical data collection varied across the twostates, which can impact the accuracy of load forecasting models. In Odisha, electricity load data were collected every hour for a period of five years (January 2018 to December 2022). On the other hand, in Delhi, electricity load data was collected every 30 minutes for a period of two years (January 2019 to December 2022). It is important to note that the difference in data collection intervals and durations can influence the accuracy of load forecasting models, and thus, careful consideration must be given to selecting an appropriate time interval and duration for data collection. The variables collected for both states included Wet Bulb Temperature, Precipitation, Dew/Frost Point, Normal Temperature, Relative Humidity, Specific Humidity, and Wind Speed. Data cleaning and transformation were performed for both datasets to resolve any missing values and integrate multiple files into a usable format. Additionally, data reduction techniques were applied to capture the essential properties of the data while removing redundancies. The forecasted response for Odisha was the load demand (in MW) for a durationof 12 months, whereas, for Delhi, it wasthe load demand (in MW) for a duration of 9 months. Regression analysis and a hybrid deep learning model utilizing a 1D CNN BI LSTM architecture were employed for load forecasting in Orissa. In contrast, Delhi's load forecasting models included Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM), Exponential Gaussian Process Regression (GPR), and a hybrid deeplearning approach. The training, validation, and testing set for Odisha comprised a time interval of 1 hour, with a total of 1,819 rows and 6 columns. The training set consisted of 70ofthe data, corresponding to 1,273 rows from January 2018 to June 2021 (42 months). The validation set contained 10% of the data, consisting of 181 rows from July 2021to December 2021 (6 months). The remaining 20% of the data formed the testing set, with 363 rows from January 2022 to December 2022 (12 months). For Delhi, the time interval was set to day-wise, resulting in a total of 1,425 rows and 6 columns. The training set constituted 70% of the data, comprising 997 rows from January 2019 to August 2021 (32 months). The validation set contained 10% of the data, consisting of 142 rows from September 2021 to December 2021 (4 months). The testing set included20% of the data, with 285 rows from January 2022 to September 2022 (9 months). Overall, this analysis reveals differences in dataset size, the time interval for data collection, and forecasted response between Odisha and Delhi. These variations canbe attributed to the unique energy demand patterns and requirements of each state. Odisha's diverse landscape and varying load patterns across different regions necessitate customized load forecasting models. On the other hand, Delhi's high population density and a large number of commercial and industrial establishments demandaccurate load forecasting to effectively manage its electricity distribution and ensure reliable power supply.

V. Conclusion

In conclusion, this comparative analysis of long-term electricity forecasting in Odisha and Delhi has provided valuable insights into their load forecasting models, dataset characteristics, and forecasted responses. The study revealed that Odisha exhibitsdiverse load patterns across different regions, while Delhi's high population density and commercial/industrial establishments impact load forecasting. The load forecasting models employed in Odisha included regression analysis anda hybrid deep learning approach, whereas Delhi utilized Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM), Exponential GPR, and a hybrid deep learning approach. Notably, the forecasted response differed between the two states, with Odisha focusing on load demand for 12 months and Delhi considering a 9-month duration. These variations in dataset size, time intervals, and forecasted response reflect the unique energy demand patterns observed in each state. Short-term load forecasting presented challenges for both states, particularly due to the volatile nature of commercial and industrial consumers in Maharashtra and Delhi. Telangana's rapid growth and investments in smart grid technologies influenced load forecasting, while Odisha's diverse consumption patterns necessitated efficient short-load forecasting models. Additionally, a statistical framework was proposed to address uncertainty in electricity forecasting models, benefiting Load Dispatch Centers in Maharashtra, Telangana, Odisha, and Delhi. This framework considers factors such as high demand, rapid growth, diverse consumption patterns, and high population density. In summary, this research paper introduced a novel hybrid deep learning model forlong-term load forecasting in power systems management. The model, incorporating afeature extraction module, a densely connected residual block (DCRB), a bidirectional long short-term memory layer (Bi-LSTM), and ensemble thinking, outperformed CNN- based models in accurately forecasting electricity load. The model's feature extraction capabilities extend beyond load forecasting andcan contribute to optimal energy allocation, demand-side management, and smart grid operation. Accurate load forecasting enhances resource optimization, blackout risk mitigation, and power supply reliability. Moreover, the model holds potential for applications in other domains such as stock price forecasting, weather prediction, and traffic flow prediction. Nevertheless, this research has limitations, including reliance on a single dataset that may not represent all power systems and the model's requirement for extensive training and computational complexity, limiting its realtime application. Future work involves exploring alternative deeplearning methods and optimizing the model's parameters to enhance accuracy. Further analysis of factors influencing electricity load will deepen the understanding of time series data, while applyingthe model to different power systems and datasets will assess its generalizability and robustness. In conclusion, this comparative analysis highlights the superiority of the proposed hybrid deep learning model over existing CNN-based models for long-term load forecasting in Orissa and Delhi. The findings contribute significantly to power systemmanagement, and further research can focus on improving accuracy and expanding the model's applications across various domains.

Acronyms and Abbreviations

Long-Term Load Forecasting	LTLF
Densely Connected Residual Block	DCRB
Root Mean Square Error	RMSE
Northern Region Load Dispatch Center	NRLDC
Odisha Power Transmission Corporation Limited	OPTCL
Megawatts	MW
One-Dimensional Convolutional Neural Network	1D CNN
Bidirectional LSTM	BI LSTM
Short-Term Load Forecasting	STLF
Autoregressive Integrated Moving Average	ARIMA
Temperature at 2 Meters (C)	T2M
Relative Humidity at 2 Meters (%)	RH2M
Specific Humidity at 2 Meters (g/kg)	QV2M
Wind Speed at 10 Meters (m/s)	WS10M
Wet Bulb Temperature at 2 Meters (C)	T2MWET
Dew/Frost Point at 2 Meters (C)	T2MDEW
Artificial Intelligence	AI
Convolutional Neural Networks	CNNs
Recurrent Neural Networks	RNNs
Rectified Linear Unit	ReLU

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Conflict of Interest

The authors have no conflict of relevant interest to this article can be used.

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